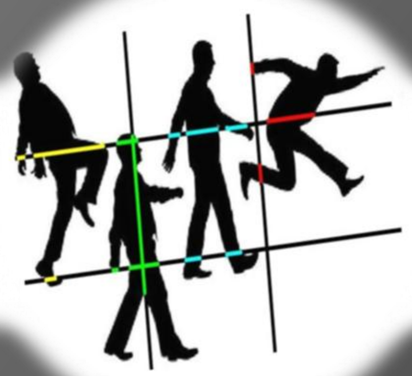

Activity Recognition using Cell Phone Accelerometers

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Abstract

Smart cell phones now incorporates many powerful sensors.

- GPS sensors
- Vision sensors (i.e., cameras)
- Audio sensors (i.e., microphones)
- Light sensors
- Temperature sensors
- Direction sensors(i.e., magnetic compasses)
- Acceleration sensors (i.e., accelerometers)

Evaluation:

- System that uses phone-based accelerometers to perform activity recognition(physical activity).
- 29 (twenty-nine) users daily activities; such as walking, jogging, climbing stairs, sitting, and standing

Applications:

- Customization of device behavior according to users activity
- Generating a daily/weekly activity

Introduction (1/3)

- Used one sensor i.e; Accelerometer of smart phone for identifying the activity that performed by user.
- Chosen Android Based Cell Phone
- In this work data was collected directly from files stored on the phones via a USB connection
- All new smart phones contains *tri-axial accelerometers* that measure acceleration in all 3 spatial dimensions. Also capable of detecting the orientation.

Introduction (2/3)

Applications

In fact there are many other applications of accelerometer if it can be used to recognize users activity

- Generate Daily/weekly reports and automatically email them to users, for estimated amount of calories to loss or gain.
- Changing the behavior of Cell phone if user is exercising (upbeat music when user is running, or sending calls directly to voicemail)

We can expect many applications which requires to change the behavior of cell phones according to users activities

Introduction (3/3)

It uses supervised learning to perform activity recognition task, steps involved in Activity recognition are as following:

1. Collect accelerometer data from twenty-nine users
2. Aggregated this raw time series accelerometer data into examples (where each example is labeled with the activity that occurred while that data was being collected)
3. built predictive models for activity recognition using three classification algorithms.

- Bao & Intille in year 2004 used bi-axial accelerometers placed in five locations on the user's body to recognize twenty activities
- But in this research they used a single device conventionally kept in the user's pocket and requires no additional actions by the user.

Contributions

- The Data which collected and continue to collect, is planed to make it public in the future.
- Raw time series accelerometer collected data can be used to transform in examples by using classification algorithms
- Used commonly available equipment, and achieved highly accurate results.
- Bring attention on data mining of wireless sensor data.

The Activity Recognition task

- Data Collection
- Feature Generation & Data Transformation
- The Activities

Data Collection

- For our task, it was necessary to have a large number of users carry an Android-based smart phone while performing certain everyday activities.
- The data collection was controlled by an application we created that executed on the phone. This application allows to record the user name, start and stop options, and label the activity being performed

- The data collection was supervised by one of the WISDM team members to ensure the quality of the data.
- Obtained approval from the Fordham University IRB (Institutional Review Board) because the study involved experimenting on human subjects

Feature Generation & Data Transformation (1/2)

Standard classification algorithms cannot be directly applied to raw time-series accelerometer data. instead, we first must transform the raw time series data into examples

- Divided the data into 10-second segments
- generated features that were based on the 200 readings
- ED = each 10 sec Data segment contains 200 features (Where ED is example Duration)

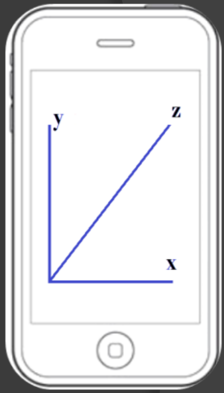
10 seconds are sufficient to capture several motions.

Also Compared10-second and 20-second ED and the 10-second ED yielded slightly better results

Feature Generation & Data Transformation (2/2)

- Generated informative features based on the 200 raw accelerometer readings (where each reading contained x, y & z value)
- Generated a total of forty-three summary features
- And 43 features are variant of following 6 features

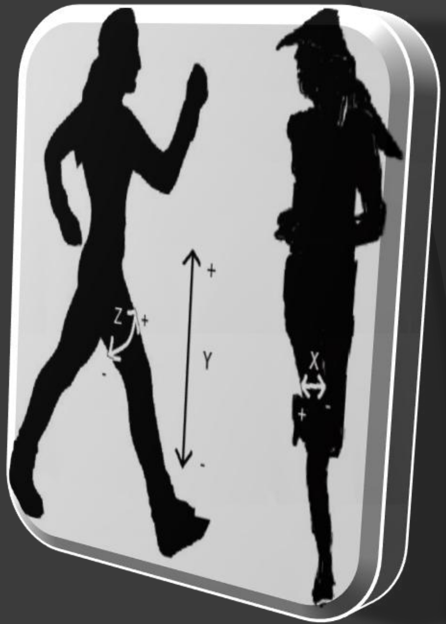
1. Average - (for each axis)
2. Standard Deviation - (for each axis)
3. Average Absolute Difference - between the value of each of the 200 readings within the ED and over those 200 values (for each axis)
4. Average Resultant Acceleration - $\sqrt{(x_i^2 + y_i^2 + z_i^2)}$ over the ED for each axis
5. Time Between Peaks – Time in milliseconds, in the sinusoidal waves associated with most activities
6. Binned Distribution - Determine the range of values for each axis (maximum – minimum), divide this range into 10 equal sized bins, and then record what fraction of the 200 values fell within each of the bins.



The number of examples generated per user for each activity varies.

The Activities

- This study considered six activities:
  1. Walking
  2. Jogging
  3. Ascending stairs
  4. Descending stairs
  5. Sitting
  6. Standing

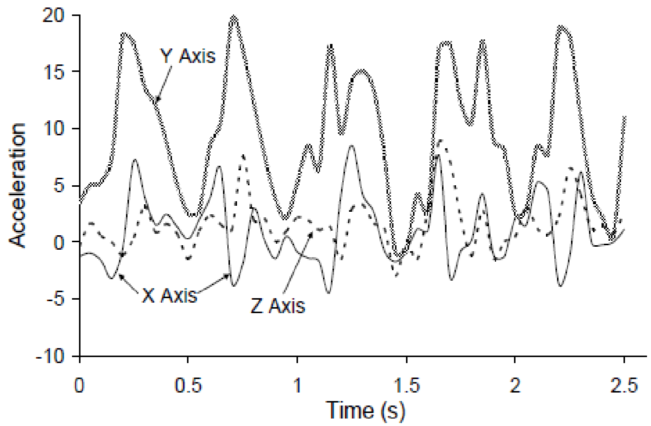


Data was recorded in 3 axis (x, y & z)

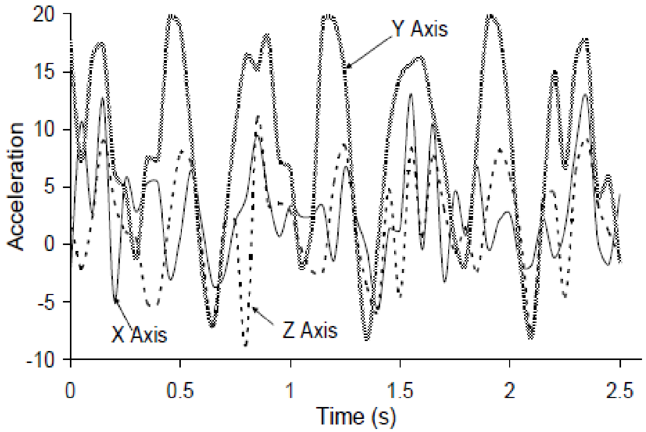
- z-axis to captures forward movement of the leg
- y-axis to captures the upward and downward motion.
- x-axis to captures horizontal movement of the leg.

Walking & Jogging Activity

- Walking:
  - a series of high peaks for the y-axis, spaced out at approximately ½ second intervals
  - z-axis with lower magnitude
  - Distance between the peaks of the z-axis and y-axis data represent the time of one stride.
- Jogging:
  - similar trends are seen for the z-axis and y-axis data but the time between peaks is less (~¼ second)
  - y-axis acceleration values for jogging is greater than walking



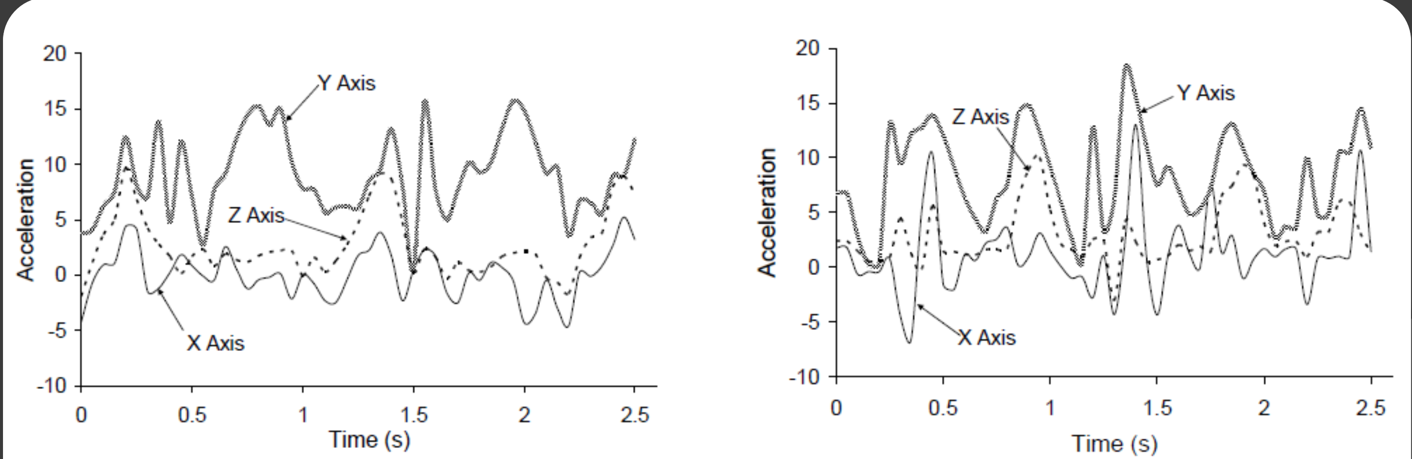
(a) Walking



(b) Jogging

Ascending & Descending Stairs Activity

- Descending:
  - series of small peaks (movement down a single stair) for y axis acceleration that take place every ~½ second
  - The x-axis data shows a series of semi-regular small peaks (between positive and negative values)
- Ascending:
  - peaks for the z-axis data and y-axis data a well spaced approximately ~¾ seconds apart (reflecting the longer time it takes to climb up stairs)

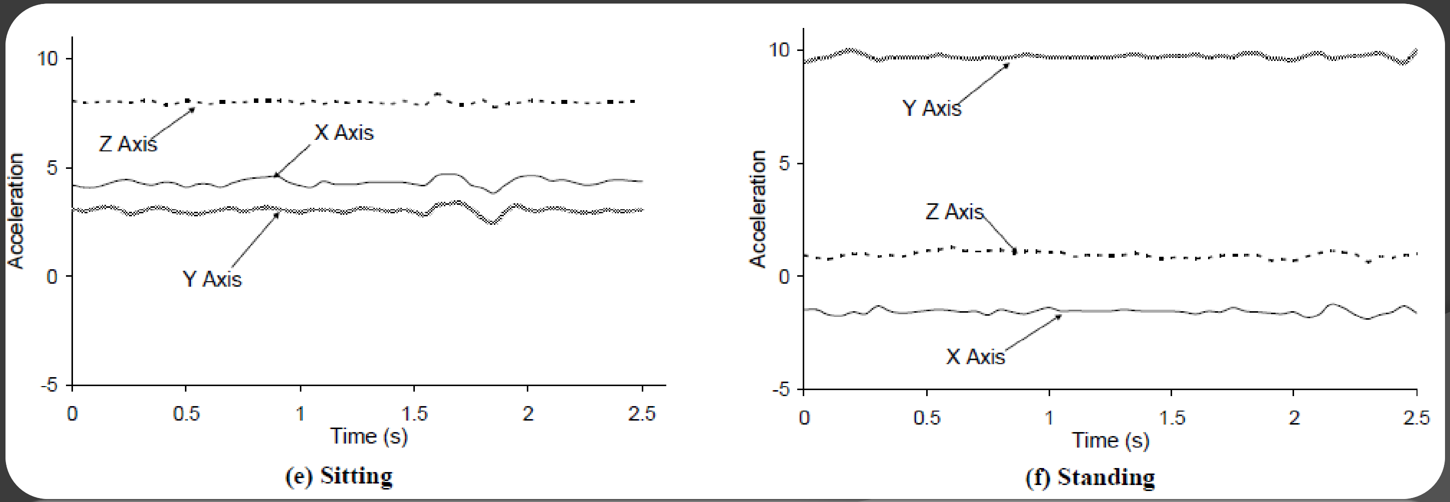


(c) Ascending Stairs

(d) Descending Stairs

Sitting & Standing Activities

- All of the acceleration values are relatively constant.
- Primary differences between these activities is the relative magnitudes of values for each axis, due to the different orientations of the device with respect to the Earth when the user is sitting and standing Thus it appears easy to differentiate between sitting and standing,



Experiments

- Table on right is subsequently used for training and testing.
- The last row in Table 1 shows the percentage of the total examples associated with each activity.
- Once the data set was prepared, we used 3 classification techniques for WEKA:
  - Decision trees (J48)
  - Logistic regression
  - Multilayer neural networks

Table 1: Number of Examples per User and Activity

ID	Walk	Jog	Up	Down	Sit	Stand	Total
1	74	15	13	25	17	7	151
2	48	15	30	20	0	0	113
3	62	58	25	23	13	9	190
4	65	57	25	22	6	8	183
5	65	54	25	25	77	27	273
6	62	54	16	19	11	8	170
7	61	55	13	11	9	4	153
8	57	54	12	13	0	0	136
9	31	59	27	23	13	10	163
10	62	52	20	12	16	9	171
11	64	55	13	12	8	9	161
12	36	63	0	0	8	6	113
13	60	62	24	15	0	0	161
14	62	0	7	8	15	10	102
15	61	32	18	18	9	8	146
16	65	61	24	20	0	8	178
17	70	0	15	15	7	7	114
18	66	59	20	20	0	0	165
19	69	66	41	15	0	0	191
20	31	62	16	15	4	3	131
21	54	62	15	16	12	9	168
22	33	61	25	10	0	0	129
23	30	5	8	10	7	0	60
24	62	0	23	21	8	15	129
25	67	64	21	16	8	7	183
26	85	52	0	0	14	17	168
27	84	70	24	21	11	13	223
28	32	19	26	22	8	15	122
29	65	55	19	18	8	14	179
Sum	1683	1321	545	465	289	223	4526
%	37.2	29.2	12.0	10.2	6.4	5.0	100

Results

- Walking and Jogging, we generally achieve accuracies above 90%.
- Jogging appears easy to find as in all its predicted accuracy is above 90%
- The "straw man" strategy always predicts the specified activity
- Multilayer performing best overall

Table 2: Accuracies of Activity Recognition

	% of Records Correctly Predicted			
	J48	Logistic Regression	Multilayer Perceptron	Straw Man
Walking	89.9	**93.6**	91.7	37.2
Jogging	96.5	98.0	**98.3**	29.2
Upstairs	59.3	27.5	**61.5**	12.2
Downstairs	**55.5**	12.3	44.3	10.0
Sitting	**95.7**	92.2	95.0	6.4
Standing	**93.3**	87.0	91.9	5.0
Overall	85.1	78.1	**91.7**	37.2

Related Work(1/5)

- Activity recognition is increasingly availability for accelerometer in consumer products
- Earliest work accelerometer based activity recognition focused on the use of multiple accelerometers placed on several parts of the user’s body.
- Bao & Intille used 5 biaxial accelerometers worn on the user’s right hip, dominant wrist, non dominant upper arm, dominant ankle, and non-dominant thigh in order to collect data from 20 users to recognize their twenty daily activities.
- Accelerometer placed on the thigh was most powerful for distinguishing between activities.

Related Work (2/5)

- Krishnan collected data from three users using two accelerometers to recognize five activities
  - Walking
  - Sitting
  - Standing
  - Running
  - Lying down
- In another paper, Krishnan examined seven lower body activities using data collected from ten subjects wearing three accelerometers
- Tapia collected data from five accelerometers placed on various body locations for twenty-one users and used this data to implement a real-time system to recognize thirty gymnasium activities.
- Mannini and Sabitini used five triaxial accelerometers attached to the hip, wrist, arm, ankle, and thigh in order to recognize twenty activities from thirteen users.

Related Work (3/5)

- *Various learning methods were used to recognize three "postures" (lying, sitting, and standing) and five "movements" (walking, stair climbing, running, and cycling).*
- Foerster and Fahrenberg used data from five accelerometers in one set of experiments, 30 participants. They used hierarchical model to distinguish between postures and movements.

- *Researchers have used a combination of accelerometers and other sensors to achieve activity recognition.*
- Parkka created a system using 29 different types of sensors (including an accelerometer worn on the chest and one worn on the wrist) in order to recognize activities such as lying, standing, walking, running, football, swinging, croquet, playing ball, and using the toilet in specific locations.

Related Work (4/5)

- Lee and Mase created a system to recognize a user’s location and activities (sitting, standing, walking on level ground, walking upstairs, and walking downstairs) using a sensor module that consisted of a biaxial accelerometer and an angular velocity sensor worn in the pocket combined with a digital compass worn at the user’s waist.

- Subramayana addressed similar activities by building a model using data from a tri-axial accelerometer, two microphones, phototransistors, temperature and barometric pressure sensors, and GPS to distinguish between a stationary state walking, jogging, driving a vehicle, and climbing up and down stairs.

- Maurer used “eWatch” devices(consisted of a biaxial accelerometer and a light sensor) placed on the belt, shirt pocket, trouser pocket, backpack, and neck to recognize the same six activities that we consider in our study.

- Choudhury used a multimodal sensor device consisting of seven different types of sensors to recognize activities such as walking, sitting, standing, ascending stairs, descending stairs, elevator moving up and down, and brushing one’s teeth.

Related Work (5/5)

- Other studies like this, have focused on the use of a single accelerometer for activity recognition.

- But either all studies used the special hardware device for detecting the activities or they used many sensors placed on different body parts to recognizing the user activities

- However unlike these studies, which use devices specifically made for research purposes, this method utilizes commercial devices that are widely-available without any additional specialized equipment.

Conclusions

- In this paper they described how a smart phone can be used to perform activity recognition, simply by keeping it in ones pocket.
- 90% of the time activity recognition is accurate
- This work is more convenient for all users rather than having a device specially manufactured for this purpose.
- several interesting applications can develop using this work

Future Work

- Their future work is to provide real time results, they described 2 ways for that:
  - Transfer the collected raw data to the server, server recognizes the activity and send it back to the phone.
  - Perform recognition directly on the cell phones, for privacy purpose. and it is possible because nowadays devices are more powerful

Questions

Thank You

for

Your Attention